Using AI – Neural Networks for Healthy Oceans

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Abstract- Every year, a significant quantity of plastic is dumped; the majority of this plastic ends up in our oceans and other bodies of water, affecting marine life and our environment. It would be very expensive, time-consuming, and perhaps result in significant additional carbon emissions to remove this plastic by hand. The identification of photographs and laborious site visits are the main methods used to identify plastic contamination in the ocean. To solve this problem, we have been using deep-learning algorithms and AI and computer vision research since the late 2010s. To make this procedure simpler, researchers have been working on machine-learning approaches. Using CNNs (convolutional neural networks), a form of deep learning architecture of neural networks used for image processing and recognition in computer vision applications, to facilitate deep learning. Listening and learning about humpback whales using AI. Whales communicate using sound in all species. Certain vocalizations are exclusive to a species or perhaps to the population in that area. Although many whales are difficult to see with the naked eye, their underwater sounds may be heard for a great distance.

We can follow the behavior and detect any unexpected noises by employing passively acoustic monitoring of the sounds generated by marine animals, such as humpback whales, to observe their natural behavior. We can track migration patterns and analyze population shifts over time. Using a convolutional neural network trained on deep learning to detect humpback whale singing in more than 187,000 hours of recorded audio.

Keywords: CNN, neural networks, acoustic monitoring, deep learning, artificial intelligence

I. INTRODUCTION (*PROBLEM STATEMENT*)

Every year, more than 400 million tons of plastic are manufactured for many applications. Every year, at least 14 million tons of plastic enter the ocean; of all marine trash, plastic accounts for 80% across surface waters to deep-sea sediments. Plastic waste entangles or is consumed by marine life, causing serious harm or even death. Human health, tourism along the coast, the quality and safety of food, and climate change are all at risk from plastic pollution. Every year, a significant quantity of plastic is dumped; the majority of this plastic ends up in our oceans and other bodies of water, affecting marine life and our environment. It would be very expensive, time-consuming, and perhaps result in significant additional carbon emissions to remove this plastic by hand. The identification of photographs and laborious site visits are the main methods used to identify plastic contamination in the ocean.

II. OBJECTIVE

A. Objective (Aim)

By using AI to reduce plastic waste and enhance marine ecosystems and aquatic life, we want to save ocean habitats. By identifying plastic utilizing various AI algorithms, strong networks, data analysis, and prediction, we want to reduce the amount of plastic in the ocean. The establishment of a thorough knowledge of the condition of marine ecosystems today via the analysis of data obtained by artificial intelligence technology.

B. Using AI to detect and analyze humpback whale sounds

To solve this problem, we have investigated and used deep learning methods, computer vision, and artificial intelligence. Using CNNs (convolutional neural networks), a form of a deep neural network architecture for image processing and recognition in computer vision applications, to facilitate deep learning. To preserve the equilibrium of marine ecosystems, we develop an effective model to assist in the removal of plastic and track the behavior of marine animals, such as humpback whales.

III. MOTIVATION

By 2030, the United Nations (UN) has set 17 sustainable development goals (SDGs) to be accomplished. All people and organizations have a shared obligation to strive toward

this objective. "Life Below Water" is one of the 17 Sustainable Development Goals. The conservation and sustainable use of the seas, oceans, and marine resources is the focus of Goal 14, "Life Below Water." Seas and oceans in good health are vital to human life and the planet's survival. The ocean is essential to our existence on the planet. Comprising 77% of the planet's surface, they hold 97% of its water and, by volume, constitute 99% of all living space on Earth. Their coastal habitats serve as storm-damage buffers, and they provide essential natural resources like food, medicine, biofuels, and other items. They also assist in the breakdown and elimination of garbage and pollutants. They serve as the largest carbon sink on Earth as well. The seas sustain life on our planet and control the climate system worldwide. With approximately one million known species living there, it is the biggest ecosystem in the world and offers a wealth of unrealized scientific research potential.

A. Overview

A sustainable future depends on the careful handling of this vital global resource. This entails boosting financing for ocean research, stepping up conservation initiatives, and acting quickly to protect the planet's greatest environment. Inspired by this, our goal is to use Artificial Intelligence (AI), primarily Neural Networks, to safeguard and protect ocean water bodies, marine ecosystems, and aquatic life.

B. Scope

- Geographical Coverage - The goal of our project is to collect information and assess the condition of aquatic ecosystems in various regions of the world, such as seas, oceans, and coasts.
- Data Collection Methods - Satellite photography, drones with underwater cameras and sensors, and visual recognition algorithms are just a few of the techniques we'll use to gather data.
- Collaboration and Partnership **-** To acquire information and create successful conservation plans, the initiative will work with governments, non- governmental organizations, and academic institutes.
- Long-Term Goals – We want to use technology to help conserve marine biodiversity by creating solutions that can be expanded, duplicated, and embraced by other groups and communities.

C. Literature Survey

Our research team's main goal is to offer data-driven insights that will enable us to choose the best sites for cleaning activities. We're making precise maps of plastic density in distant ocean places thanks to new technology and artificial intelligence (AI) technologies. The present datasets were constructed using less usual techniques (airplane), which are very expensive and difficult to arrange, or labor-intensive standard techniques (trawls). The most crucial component of any effort to use machine learning is undoubtedly having enough high-quality data since all machine learning algorithms need data to be trained.

Computer vision algorithms relying on supervised machine learning are often taught using data types corresponding to the expected output. For instance, a picture is an input for object identification, and the result is a collection of bounding boxes and class labels. A collection of pictures is required to train an object detector, and each image in the dataset must include bounding boxes around objects and the associated class labels.

D. Techniques and Algorithms

- Picture classification, object identification, and picture segmentation are the tasks involved in computer vision and deep learning.
- Data Gathering for Waste Plastic Detection - Supervised Computer vision algorithms that rely on machine learning are often taught using the same types of inputs they anticipate receiving as output.
- For instance, a picture is an input for object identification, and the result is a collection of bounding boxes and class labels. A collection of pictures is required to train an object detector, and each image in the dataset must include bounding boxes around objects and their associated class labels.
- Preparation of Data and Model Training: After constructing our dataset, we divide our data to train, verify, and test subsets. Generally, the ratio used for splitting is 70–15–15, or 70% training data to 15% verification and test data.
- We could also split them with 60–20–20 or even 50–25–25, it depends on a variety of factors but the best ratio for a specific problem is generally found through trial and error.
- Depending on several variables, we may divide them

into 60–20–20 or even 50–25–25; nevertheless, trial and error often discover the optimal ratio for a given situation.

- Deep machine learning analyzes long-term passive acoustic data of whale sounds.
- An established method for studying the distribution, migration patterns, and ecology of a broad range of marine mammal species is passive acoustic monitoring. The amounts of passive acoustic information acquired have expanded rapidly due to advancements in technology and data gathering; as a result, the time needed for analysis has become the limiting factor in discoveries rather than the amount of data collected.
- To overcome this constraint, we train a deep convolutional neural network(CNN) to recognize humpback whale songs in more than 187,000 hours of acoustic data gathered over 14 years at 13 distinct monitoring stations in the North Pacific.
- Convolutional neural networks, including YOLO (You Only Look Once), Region-Based Convolutional Neural Networks (R-CNN), and Fast R-CNN.

IV. ALGORITHMS

Region-Based Convolutional Neural Networks, or R-CNNs,

R-CNN (Region-based CNN) to address this object detection problem. The selective search technique used in this R-CNN architecture produces around 2000 region recommendations. After that, the CNN architecture, which computes CNN features, receives these 2000 region suggestions. After that, an SVM model is trained using these attributes to categorize the item included in the area of the proposal. A box with a boundary regressor is used as an additional step to locate the items in the picture.

YOLO (You Only Look Once)

Compared to many other CNN-based object identification algorithms, YOLO is a real-time object detection system that is quicker and more accurate. While many CNN-based algorithms can only recognize one item at a time, YOLO can detect many things in a single picture. YOLO, which stands for "You Only Look Once," is a well-liked class of real-

time object identification algorithms used by the biggest tech firms in computer vision for many of their commercial products. When the first YOLO object detector was introduced in 2016, the new architecture outperformed all others in speed.

A. System Architecture

Because of how the System Architecture is built, the model illustrates how we may find plastic in the water and teach it to recognize various kinds of plastic so that different trash can be separated. This makes it easier to identify the kind of plastic that gets into the water and aids in its removal.

1. *The objective is to use deep learning and machine learning to create a data model that can recognize and detect various kinds of plastic, beginning with data preparation.*
2. *Remote Sensing Spectral Indices (indices including NDVI, FDI, PI, etc.) are supplied datasets into the model to examine the plastic index.*
   i) *Finding and Identifying Marine Floating Plastic*
   ii) *Supervised modeling involves using various AI algorithms for model testing and training.*
   iii) *System Flow: A system flow is a model of a system that illustrates the choices and actions that the system makes. Because they graphically depict the back-and-forth interactions between systems and complicated branching, they help comprehend complex system interactions.*

B. Use Case Diagram

A use case diagram is a sequence of events or activities describing how an actor and system interact to accomplish a task. The name of the use case is shown as an ellipse. The name appears underneath the stick figure depiction of the actor. An actor graph is a use-case diagram.

The User and the System are the actors in the use case diagram.

- Actors indicate the project's Use Cases with arrows.
- Using an image as input, segmenting and detecting, object detection using CNN, object labeling, ocean dataset, floating plastic dataset,
- The user's use cases include data normalization and the output (Image created Analyzing the kind of plastic type).
- The way a user interacts with a computer is by entering a picture.
- Picture preprocessing is when the system scans the

picture the user inputs.

- The computer utilizes a convolutional neural network (CNN) and a trained object detection model that uses Faster CNN/Yolo v5 and CNN to identify things in the user-supplied picture.
- The appropriate item for the user picture is generated as an output using the data from CNN and the algorithms.

Sequence diagrams clarify a system's design and define different system needs. Sequence diagrams are quite helpful since they display the interaction logic is the temporal sequence of interactions amongst the system's objects.

C. Class Diagrams

In the unified modeling language, a class diagram represents the connections between classes and a form of static structural attribute. Three divisions in a rectangle are used to symbolize it. The operations are in the bottom compartments, the characteristics are in the middle compartment, and the class name is in the top compartment.

Activity diagrams are visual aids for workflows that show sequential actions and activities supporting concurrency, choice, and iteration. Activity diagrams in the Unified Modeling Language (UML) depict system components' step- by-step operational and business processes. The entire flow of control and activity is shown in an activity diagram as a rounded box with the name of the Action.

- The way a user interacts with a computer is by entering a picture.
- The system does what is known as "extraction of EXIF timestamp and automatic horizon detection and camera orientation" by searching the user-input picture for all files.

A deployment diagram models the actual placement of artifacts on deployment targets in the unified modeling language. Diagrams of deployment indicate the distribution.

Distributing artifacts to nodes by the mutually established deployments. A three-dimensional box symbolizes the object. A relationship between communication and dependency is depicted.

The primary component of deployment is image captioning, which involves using a device like a user desktop to take an image as input and perform various tasks like object detection, segmentation and

detection, faster R-CNN and YOLO, data normalization, and output (the type of plastic image that is produced as a result of the analysis).

V. ALGORITHMS

- The computer utilizes YOLO v5 (You Only Look Once) and Faster R-CNN (Faster Regional Convolutional neural network) to identify plastic in the user-supplied picture.
- The system generates the required item detection (by evaluating the kind of plastic) for the user picture as output using the CNN data.
- Fast R-CNN: Using a methodology similar to the R-CNN algorithm, Fast R-CNN was developed to create an object identification algorithm that operates at a quicker pace. However, to create a convolutional feature map, we feed the input picture to the CNN rather than the region recommendations. We extract the area of suggestions from the convolutional feature map, warp them into squares, and then restructure them into a fixed size using an ROI pooling layer to feed them into a fully connected layer.
- We use a SoftMax layer to forecast the suggested region's class and the bounding box offset values based on the ROI feature vector. "Fast R-CNN" outperforms R-CNN since it doesn't need you to constantly feed the CNN or convolutional neural network with 2000 region ideas.
- Instead, a feature map is produced from the convolution process, which is only performed once per picture.
- Since then, YOLO has been published in several versions and variations, all of which substantially boost efficiency and performance. There have been multiple debates since several research teams published their versions of YOLO, such as YOLOv5. YOLOv4 represents an enhanced iteration of YOLOv3. Three key breakthroughs are cross-mini- batch normalization, self-adversarial training, and mosaic data improvement. YOLOv7 is the most accurate and quickest real-time object identification model for computer vision applications.

- Selective Search
  1. Create the first sub-segmentation; we produce a large number of potential regions

2.　Recursively merge comparable sections into bigger ones using a greedy approach

3.　Create the final candidate region suggestions using the regions that were produced.

To ease the identification of plastic garbage, we have designed and implemented deep learning models that consider object recognition and quicker R-CNN and YOLO v5 approaches. Data analysis between the created and real models was used to assess the various models' results.

Using passive acoustic monitoring to listen for and analyze humpback whale noises, one may track the behavior of marine animals. Our assessment studies show that object identification with assistance and humpback whale song analysis outperform their models.

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